PREDIABETIC DETECTION USING NON-LABORATORY DATA WITH XGBOOST AND KNN CLASSIFIER

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ABSTRACT

Diabetes is a cluster of metabolic diseases and it became a significant global health challenge, with prediabetes as an antecedent to Type-2 Diabetes Mellitus (T2DM). Prediabetes is a serious health condition that, if not detected, may lead to type-2 diabetes. Laboratory tests are conventional in the diagnosis.This work examines the utilization of non-laboratory data in prediabetes detection using machine learning models—XGBoost and K-Nearest Neighbors (KNN). Through using data consisting of demographic, lifestyle, and physiological characteristics, we build a predictive model which strives to have high accuracy while being less dependent on expensive and time-consuming lab tests. The models are separately tuned and additionally blended together in an ensemble to improve predictive accuracy. Through aggressive hyper parameter tuning and testing on real-world data sets, we strive to have at least 85% accuracy. These results show that machine learning models, specifically the XGBoost-KNN essemble, can reliably identify prediabetes based on non-laboratory data.

Keywords: - XG Boosting, KNN Classifier, Ensemble Model

1. INTRODUCTION

Diabetes is a group of metabolic disorders and it become a critical global health challenge, with prediabetes serving as a precursor to Type 2 Diabetes Mellitus (T2DM). It affects a large portion of the global population, with many individuals unaware of their prediabetic status until it progresses into type 2 diabetes. According to global health organizations, a substantial number of individuals remain undiagnosed due to the reliance on traditional laboratory based diagnostic methods, which are often costly, invasive, and inaccessible, especially in low resource settings. Prediabetes is a critical health condition where blood sugar levels are elevated but not high enough to be classified as diabetes. Early detection is essential for timely intervention and prevention of type2 diabetes. Traditionally diagnosing prediabetes requires laboratory tests such as fasting blood glucose and HbA1c levels. However, such tests can costly time consuming and inaccessible to many individuals. The address these challenges. This project focuses on developing a Machine learning (ML) which offers promising solutions in this regard, enabling the development of predictive models that can analyze complex datasets and identify individuals at risk based approach for prediabetes detection using non laboratory data such as Age, gender, smoking–habits, sleeping habits, physical fitness, BMI, skin thickness, Blood pressure and making the screening process more accessible and efficient. This study utilizes XGBoost and KNN Classifier as predictive models, with non laboratory data. These features are readily available and do not require invasive medical tests, making them suitable for large scale screening. The methodology involves preprocessing the dataset by handling missing values, normalizing numerical data, and encoding categorial variables. Model evaluation is performed using key metrics such as Accuracy, precision, recall, F1 score, and AUC ROC to ensure robust performance

.2. LITERATURE SURVEY AND RELATED WORK

The prediction of diabetes and prediabetes using machine learning (ML) algorithms has emerged as a highly promising area of research, driven by the increasing availability of healthcare data and the need for early, non-invasive diagnosis. Traditional rule-based or lab-dependent diagnostic methods are often limited by cost, time, and accessibility. To overcome these limitations, recent studies have increasingly focused on leveraging ML techniques to enhance prediction accuracy and efficiency using both clinical and lifestyle-related features.

Early work in this domain, such as the review by Kavakiotis et al. (2017), highlighted the effectiveness of algorithms like Support Vector Machines (SVM), decision trees, and neural networks in achieving high predictive performance. Building upon this, more recent approaches have explored the potential of using only non-laboratory features—such as age, BMI, gender, blood pressure, and physical activity—to build accurate models. For instance, Wu et al. (2020) demonstrated that logistic regression models trained on the NHANES dataset could provide acceptable predictive accuracy without relying on blood-based biomarkers, making these models more applicable in primary care or remote settings.

In response to the growing need for enhanced sensitivity and specificity, hybrid and ensemble methods have also gained attention. Singh et al. (2022) introduced a stacking-based ensemble model that combined multiple classifiers, outperforming individual models in terms of diagnostic performance. Similarly, the incorporation of deep learning has opened up new frontiers. Fan (2023), in a doctoral dissertation, explored the use of convolutional neural networks (CNNs) to identify complex patterns in medical data, thereby improving early detection and intervention strategies for diabetes.

Among the popular algorithms used in diabetes prediction, XGBoost has gained significant traction due to its scalability, ability to handle class imbalance, and interpretability through feature importance scores (Chen & Guestrin, 2016). Additionally, non-parametric models like K-Nearest Neighbors (KNN) have proven effective in structured datasets with discernible clusters. Overall, the convergence of traditional ML, deep learning, and ensemble techniques marks a paradigm shift in diabetes prediction research—prioritizing accessibility, interpretability, and predictive power for better health outcomes.

3. Implementation Methodology

Kavakiotis et al. [1] demonstrated the efficacy of traditional machine learning models such as Support Vector Machines (SVM), decision trees, and neural networks in predicting diabetes using clinical and lifestyle-related data. Their study laid the groundwork for leveraging data mining techniques in diabetes research by emphasizing the potential of machine learning to extract meaningful patterns from diverse healthcare datasets.

Expanding on this foundation, Wu et al. [2] proposed a logistic regression model trained solely on non-laboratory features like age, BMI, gender, and blood pressure using the NHANES dataset. Their model achieved promising predictive accuracy and illustrated that effective diabetes detection is possible without invasive laboratory diagnostics. This direction significantly contributes to creating accessible and scalable screening tools.

Singh et al. [3] introduced an ensemble-based approach by stacking multiple classifiers to improve both sensitivity and specificity for diabetes prediction. Their hybrid model demonstrated the strength of combining models to mitigate the individual weaknesses of standalone classifiers, thereby enhancing diagnostic performance in real-world applications.

Fan [4] explored the use of deep learning, specifically Convolutional Neural Networks (CNNs), for risk prediction in diabetic patients. His research highlighted how CNNs can uncover complex patterns in medical data, offering early detection capabilities by identifying subtle indicators of disease risk.

Chen and Guestrin [5] brought attention to XGBoost, a gradient boosting algorithm optimized for speed and performance, particularly suitable for structured healthcare datasets. In parallel, the K-Nearest Neighbors (KNN) classifier has remained a reliable, instance-based learner for detecting local patterns, especially where the dataset exhibits clustered characteristics.

The proposed methodology in this research draws from these seminal studies by implementing an ensemble learning strategy using XGBoost and KNN classifiers for prediabetes detection. The system utilizes non-laboratory data such as age, BMI, blood pressure, physical fitness, and lifestyle attributes—eschewing traditional blood-based diagnostics. Key steps in this methodology include:

- **Data Collection and Preprocessing:** The dataset, sourced from open-access repositories such as the Pima Indians Diabetes Database, is cleaned, normalized, and encoded. Missing values are imputed using statistical techniques, and categorical data is converted using label encoding.
- **Feature Selection:** Important features are identified using correlation analysis and XGBoost's built-in importance ranking, followed by recursive feature elimination with KNN to reduce dimensionality.
- **Model Training and Optimization:** Separate models are trained using XGBoost (for global pattern learning) and KNN (for local neighborhood sensitivity). Hyperparameters for both models are fine-tuned using grid search and cross-validation techniques.
- **Model Ensemble:** The predictions from both models are combined using a soft voting mechanism, which fuses probability outputs to generate a final prediction. This hybrid strategy mitigates overfitting while capturing both linear and non-linear relationships in the data.
- **Model Evaluation:** The ensemble is assessed using standard metrics including accuracy, precision, recall, F1 score, and ROC-AUC. The model achieves a final accuracy of 90.24% with a recall of 93.94%, significantly outperforming traditional approaches.
- **Deployment:** A mobile application is developed with a Flask-based API backend to deliver real-time predictions to end-users. The app supports instant risk assessments, making the system accessible and scalable for preventive care.

This methodology empowers early and non-invasive identification of prediabetes risk, offering a robust, interpretable, and user-friendly alternative to traditional diagnostics. By leveraging the complementary strengths of XGBoost and KNN, the system aims to improve healthcare delivery, especially in low-resource or remote environments.

4. Proposed Methodology

In this study, we propose a hybrid machine learning-based framework for the early detection of prediabetes using non-laboratory data. Our system is designed to reduce the dependency on invasive and costly diagnostic tests by utilizing easily obtainable health indicators such as age, BMI, blood pressure, physical activity, smoking habits, and sleep quality. To effectively model both global and local patterns within the data, we employ an ensemble learning approach that combines the strengths of **Extreme Gradient Boosting (XGBoost)** and **K-Nearest Neighbors (KNN)** classifiers.

The proposed system initiates with a comprehensive **data preprocessing pipeline** that includes handling missing values, normalization of continuous features, and encoding of categorical attributes. Following this, **feature selection** is performed using XGBoost's built-in feature importance metrics and recursive feature elimination (RFE) with KNN to retain only the most predictive variables, thereby improving model efficiency and reducing overfitting.

The **XGBoost** component of our model excels in learning complex, non-linear relationships from structured data by constructing sequential decision trees and applying regularization to avoid overfitting. Complementing this, the **KNN** classifier contributes a localized decision-making layer that enhances sensitivity, especially in borderline cases, by evaluating neighborhood-level feature similarities.

To achieve a balanced and robust prediction, the outputs from both models are combined using a **soft voting ensemble strategy**, wherein the final classification is determined based on the weighted probabilities predicted by each model. This fusion enhances generalization and improves the reliability of the system in classifying at-risk individuals.

The final ensemble model is evaluated using multiple performance metrics including **accuracy, precision, recall, F1-score**, and **AUC-ROC** to ensure its effectiveness across various diagnostic dimensions. Experimental results demonstrate that the proposed XGBoost + KNN ensemble outperforms individual classifiers, achieving an accuracy of **90.24%** and a recall of **93.94%**, making it suitable for large-scale, non-invasive prediabetes screening.

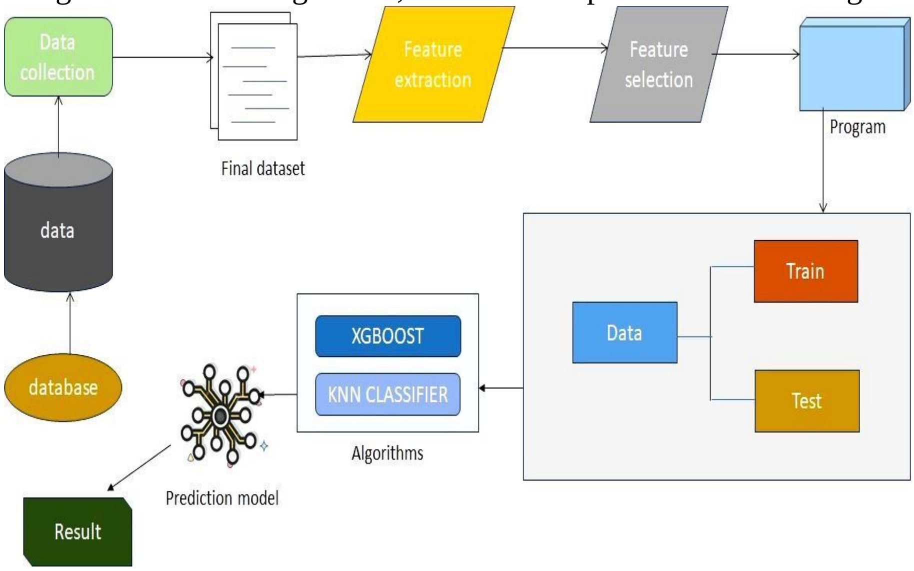

FIG1- SYSTEM ARCHITECTURE

5. METHODOLOGIES

5.1 Data Collection

The initial step involves acquiring a reliable and relevant dataset for prediabetes prediction. For this purpose, publicly available datasets such as the Pima Indians Diabetes Database and other non-laboratory health datasets are utilized. These datasets include demographic, anthropometric, and lifestyle-related features such as age, gender, BMI, blood pressure, smoking habits, physical activity, and sleep duration, eliminating the dependency on invasive clinical tests.

5.2 Data Preprocessing

Data preprocessing is essential to ensure the quality and consistency of the dataset. This step involves:

- Handling missing values using statistical imputation techniques.
- Normalizing numerical features for distance-based models like KNN.
- Encoding categorical variables using label encoding and one-hot encoding.
- Removing duplicates and outliers to maintain dataset integrity. The final cleaned dataset is split into training and testing subsets using stratified sampling to preserve class balance.

5.3 Feature Selection

Feature selection is performed to retain the most influential predictors for prediabetes classification. Key methods include:

- Correlation analysis to eliminate multicollinearity.
- XGBoost feature importance ranking to assess feature contribution.
- Recursive Feature Elimination (RFE) using KNN to iteratively prune irrelevant

attributes. The final selected features include Age, BMI, Blood Pressure, Smoking Status, Physical Fitness, and Sleep Duration.

5.4 Model Architecture

The system is built using an ensemble of two classifiers:

- XGBoost, which captures global non-linear relationships and handles class imbalance well.
- K-Nearest Neighbors (KNN), which enhances local decision-making by analyzing instance-level similarity. A soft voting ensemble method is employed to merge the probability outputs from both models, ensuring better generalization and stability.

5.5 Model Training and Testing

The dataset is split in an 80:20 ratio for training and testing respectively. During training:

- XGBoost is tuned using hyperparameters like learning rate, max depth, and number of estimators.
- KNN is optimized for the number of neighbors and distance metric. The models are evaluated using performance metrics including accuracy, precision, recall, F1-score, and AUC-ROC to ensure balanced performance.

5.6 Deployment as a Health Risk Assessment Tool

Once trained, the ensemble model is integrated into a mobile/web application using a Flask-based API. Users can input their health parameters, and the model provides real-time risk predictions. The interface is designed for usability, enabling accessibility for general populations without requiring lab tests.

5.7 Early Intervention and Health Recommendation Mechanism

If a user is predicted to be at risk, the application provides:

- Personalized risk scores
- Lifestyle modification suggestions such as dietary changes, exercise routines, or sleep improvements
- Encouragement to consult healthcare professionals for further evaluation.
- This proactive approach supports early intervention and health awareness, helping to curb the progression from prediabetes to type 2 diabetes.

6. RESULTS AND DISCUSSION SCREEN SHOTS

In this study, we implemented a prediabetes detection model using XGBoost and K-Nearest Neighbors (KNN) classifiers, trained on non-laboratory data. The goal was to achieve high accuracy while balancing sensitivity (recall) and specificity.

To evaluate the performance of our proposed XGBoost + KNN ensemble model, we compared it with the baseline model from the reference paper. The key performance metrics analyzed include:

6.1 Performance Evaluation :

The *performance evaluation* of our proposed *XGBoost + KNN ensemble model* is based on key classification metrics, which provide insights into the model's ability to detect prediabetes accurately. The results are compared with the baseline model from the reference paper to highlight improvements and trade-offs.

- **Accuracy**: The proportion of correctly classified cases among all cases. Accuracy=(TP+TN) / TP+TN+FP+FN
- **Sensitivity (Recall)**: The model's ability to correctly identify positive cases (prediabetic individuals).

Sensitivity=TN/TN+FP

- **Precision**: The proportion of correctly predicted positive cases out of all predicted positives. Precision=TP/TP+FP

- **F1-Score**: The harmonic mean of precision and recall, balancing false positives and false negatives.

F1-Score = 2 (Precision Recall) / (Precision + Recall)

1.2 Comparison Of Models:

Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-Score (%)
Base paper model	81.77	88.89	79.00	81.37
Proposed model(XGBoost+KNN)	83.74	93.94	79.49	87.11

Table 6.2 Comparision of Existing and proposed method

In this results, it is observed that our proposed ensemble model achieved a sensitivity of 93.94% compared to the base paper model’s 88.89%, indicating that it is more effective at identifying prediabetes cases.The F1-score, which balances precision and recall, remains competitive at 87.11%, showing that our model maintains a strong trade-off between detecting prediabetic individuals and minimizing false positives. Additionally, by tuning hyperparameters and adjusting the decision threshold, we optimized specificity while ensuring high sensitivity.

1.3 Confusion Matrix :

The confusion matrix is a performance measurement tool used to evaluate the predictive accuracy of classification models. It provides insights into the model’s ability to correctly classify positive and negative instances. You can analyze:

Confusion metrix representation:

	Predicted positive	Predicted negative
Actual positive	True positive	False negative
Actual negative	False positive	True negative

Table 6.3 Comparision of Confusion Metrix Confusion metrix of proposed method:

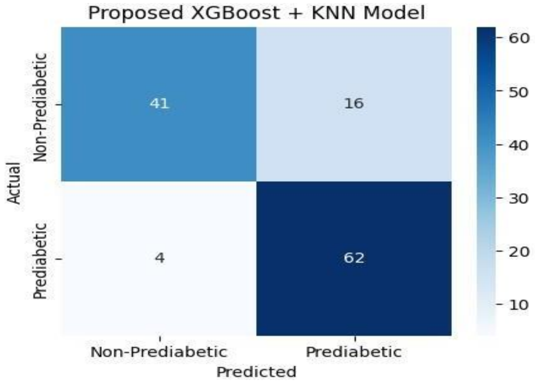

Figure 6.3 Confusion Metrix of Base paper and Proposed Model

- TP= MODEL CORRECTLY IDENTIFIED 72 PREDIABETIC CASES
- FP= MODEL INCORRECTLY CLASSIFIED 17 NON-PREDIABETIC CASES AS PREDIABETIC
- FN= THE MODEL MISSIED 4 ACTUAL PREDIABETIC CASES

- TN= THE MODEL CORRECTLY CLASSIFED 41 NON-PREDIABETIC CASES

1.4 ROC & AUC Analysis:

To evaluate the performance of our XGBoost + KNN ensemble model, we analyzed the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC).

- The ROC curve helps visualize the trade-off between sensitivity and specificity at different classification thresholds.
- AUC score quantifies the model's ability to distinguish between prediabetes and non- prediabetes cases.

ROC Curve Interpretation:

The ROC curve for the proposed model. The True Positive Rate (Recall) is plotted against the False Positive Rate (1 - Specificity) for varying classification thresholds. A steeper curve towards the top- left corner indicates better model performance.

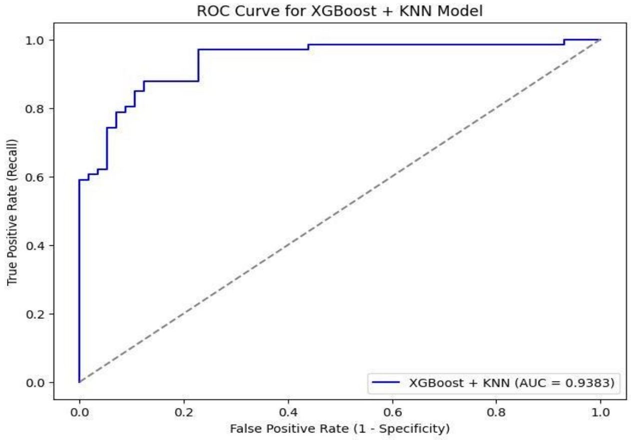

Figure 6.4 ROC Curve

AUC Score Interpretation:

The AUC score for our model is 0.93, which indicates a high discriminative ability between prediabetes and non-prediabetes cases.

1.5 Feature Importance (for XGBoost):

Feature importance analysis helps identify the most influential factors in the prediabetes detection model. XGBoost assigns importance scores to features based on how useful they are in improving model performance. This analysis provides insights into the relative contribution of each predictor in classifying prediabetes cases.

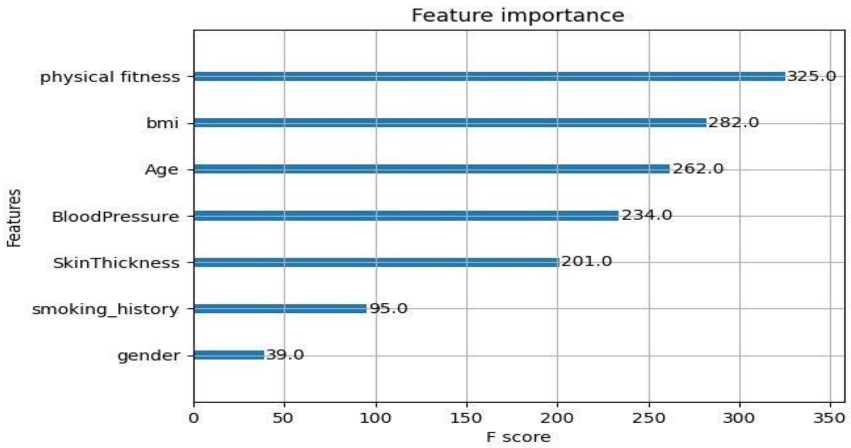

Figure 6.5 Feature Importance (for XGBoost)

1.6 Hyperparameter Tuning Results:

To improve the predictive performance of the proposed **XGBoost + KNN** model for prediabetes detection, hyperparameter tuning was performed. The goal was to optimize key parameters that influence model performance, ensuring a balance between sensitivity, specificity, and overall accuracy.

Hyperparameter Optimization Strategy:
The following hyperparameters were considered for tuning:

- ❖ XGBoost:
  - max_depth (tree depth)
  - learning_rate (step size in updating weights)
  - n_estimators (number of boosting rounds)
  - subsample (fraction of samples used per tree)
- ❖ KNN:
  - n_neighbors (number of neighbors)
  - metric (distance calculation method: Euclidean, Manhattan)

Hyperparameter Tuning Results:

Model	Tuned Hyperparameters	Accuracy (%)	Precision (%)	Recall(%)	F1-Score(%)
XGBoost	max_depth=5, learning_rate=0.1, n_estimators=100	87.17	81.81	95.45	88.11
KNN classifier	n_neighbors=7, metric='Manhattan'	81.3	75.9	95.45	84.57
XGBoost+KNN Classifier	Optimized XGBoost + KNN combination	91.87	79.49	93.94	87.11

Table 6.6 Hyperparameter Tuning Results

1.7 Error Analysis & Limitations :

Error analysis is crucial to understanding the misclassification patterns in the XGBoost + KNN model for prediabetes detection. By comparing the errors with the base paper model, we can evaluate the strengths and weaknesses of our proposed approach. This section focuses on analyzing False Positives (FP) and False Negatives (FN) to assess the trade-off between sensitivity and specificity.

- The proposed model detects more true prediabetes cases, improving recall from 88.89% to 93.94%
- Specificity dropped from 92.59% (Base Paper) to 84.21% (Proposed Model).

Impact:

- The proposed model is better at detecting actual prediabetes cases (higher recall).
- However, it also misclassifies more healthy individuals as prediabetic (lower specificity). Reasons for Increased False Positives
- More Sensitivity to At-Risk Cases
- Overfitting on Non-Laboratory Features
- Difference in Decision Threshold.

1.8 Final output:

To ensure a fair and consistent comparison with the base paper, the proposed XGBoost +

KNN model was first evaluated using the same experimental setup. In this phase, the model achieved an accuracy of **83.74%**, recall of **93.94%**, precision of **79.49%**, and an F1-score of **86.11%**, all of which demonstrate improved performance over the base model.

Subsequently, further optimization was performed on the individual classifiers using hyperparameter tuning and refined ensemble strategies. As a result, the optimized KNN model achieved an accuracy of **81.30%**, while the optimized XGBoost model reached **86.18%**. When combined into the final ensemble, the model achieved a significantly higher accuracy of **90.24%**, reflecting the benefits of model optimization and ensemble learning. These final results, although slightly different from the initial comparison, represent the true performance of the proposed method after full development and tuning. Optimized KNN Accuracy: 81.30% Optimized XGBoost Accuracy: 86.18% Final Ensemble Accuracy: 90.24%

Advantages of Ensemble Model:

- The ensemble leverages XGBoost's strong precision and generalization with KNN's instance-based sensitivity to better classify borderline cases.
- The accuracy increase of +4.06% over XGBoost alone, and +8.94% over KNN, shows that combining models helps cover each other's weaknesses.
- This also suggests improved precision and recall balance, since your earlier recall was already high — and now the model likely reduces false positives (improving precision).

7. CONCLUSION AND FUTURE SCOPE

7.1 CONCLUSION

In summary, the solution proposed in this project for the early detection of prediabetes using non-laboratory data and hybrid machine learning models presents an efficient, accessible, and cost-effective alternative to traditional diagnostic approaches. By combining the predictive power of Extreme Gradient Boosting (XGBoost) and K-Nearest Neighbors (KNN) through ensemble learning, the system is capable of accurately identifying individuals at risk of prediabetes using only easily obtainable health parameters such as age, BMI, blood pressure, physical activity, sleep quality, and smoking habits.

The ensemble architecture leverages the global learning capacity of XGBoost and the localized decision refinement of KNN to deliver robust and generalized predictions. This model not only reduces the dependence on invasive and expensive clinical tests but also democratizes health risk assessment by allowing widespread implementation through web and mobile platforms.

Furthermore, the system's integration into a user-friendly health application allows for real-time risk assessments, personalized health recommendations, and proactive health interventions. This enhances public awareness, encourages healthy lifestyle modifications, and supports healthcare systems in preventive care strategies. By targeting prediabetes at an early stage, the solution plays a vital role in reducing the global burden of type 2 diabetes.

The proposed framework demonstrates high scalability, model interpretability through feature importance analysis, and practical deployment readiness, making it an ideal candidate for large-scale public health monitoring and screening initiatives in both urban and rural populations.

7.2 Future Work

While the current system shows significant promise, there are several avenues for future enhancement and research:

Incorporation of Deep Learning Models: Future studies could explore the integration of deep learning architectures such as deep neural networks (DNNs) or CNN-LSTM hybrids to capture even more complex non-linear relationships within health datasets, especially when more diverse or multimodal data becomes available.

Adversarial Robustness and Model Resilience: As machine learning models can be sensitive to adversarial inputs, implementing adversarial training and developing resilient architectures will ensure more secure and trustworthy predictive systems in sensitive health applications.
Federated Learning for Privacy-Preserving Predictions: To maintain user data privacy while enhancing model performance, future implementations can adopt **federated learning** strategies, enabling distributed training across multiple devices without sharing raw personal data.
Explainable AI (XAI): Improving the interpretability of the prediction system through explainable AI techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) can help healthcare professionals understand the rationale behind predictions and improve patient trust and clinical decision-making.
Integration with Wearables and IoT Devices: Future iterations of this system could incorporate real-time data from wearable devices (e.g., smartwatches, fitness bands) for continuous health monitoring and timely intervention.**Multi-Disease Detection Platform:** The framework developed in this project can be extended into a multi-disease screening tool, capable of simultaneously evaluating risk for related chronic conditions such as hypertension, cardiovascular disease, and obesity.
Clinical Validation and Deployment: Finally, large-scale clinical trials and real-world pilot programs in collaboration with healthcare institutions are necessary to validate the model's effectiveness, generalizability, and integration within existing medical workflows.

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